SMART AGRI-SYSTEMS FOR THE PIG INDUSTRY

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ABSTRACT

The projected rise in the global human population and the anticipated increase in demand for meat and animal products, albeit with a greatly reduced environmental footprint, offers a difficult set of challenges to the livestock sector. Primarily, how do we produce more, but in a way that is healthier for the animals, public, and the environment? Implementing a smart agri-systems approach, utilising multiplatform precision technologies, internet of things, data analytics, machine learning, digital twinning and other emerging technologies can support a more informed decision-making and forecasting position that will allow us to move towards greater sustainability in future. If we look to precision agronomy, there are a wide range of technologies available and examples of how digitalisation and integration of platform outputs can lead to advances in understanding the agricultural system and forecasting upcoming events and performance that have hitherto been impossible to achieve. There is much for the livestock sector and animal scientists to learn from the developments of precision technologies and smart agri-system approaches in the arable and horticultural contexts. However, there are several barriers the livestock sector must overcome: (i) the development and implementation of precision livestock farming technologies that can be easily integrated and analysed without the support of a dedicated data analyst in house; (ii) the lack of extensive validation of many developed and available precision livestock farming technologies means that reliability and accuracy are likely to be compromised when applied in commercial practice; (iii) the best smart agri-systems approaches are reliant on large quantities of data from across a wide variety of conditions, but at present the complications of data sharing, commercial sensitivities, data ownership, and permissions make it challenging to obtain or knit together data from different parts of the system into a comprehensive picture; and (iv) the high level of investment needed to develop and scale these technologies is substantial and represents significant risk for companies when a technology is emerging. Using a case study of the National Pig Centre (a flagship pig research facility in the UK) we discuss how a smart agri-systems approach can be applied in practice to investigate alternative future systems for production, and enable monitoring of these systems as a commercial demonstrator site for future pork production.

Keywords: *Digital farming, Pork, Precision Livestock Farming,Production, Systems approach*

INTRODUCTION

It is projected that the global human population will increase to over 9 billion over the coming 30 years (Food and Agriculture Organization (FAO), 2011). Much of this growth is expected to take place in developing countries and it is projected that with increased development, there is likely to be an increased demand for animal products (United Nations (UN), 2019). Alongside the growing population size and demand for animal products, there is clear rising concern worldwide about human impacts on the environment. Our current livestock production systems are already unsustainable and are in urgent need of an overhaul to increase sustainability of the practices used, and, in doing so, lower the impacts on the animals, and on public and environmental health (Ochs et al., 2018). A sustainable livestock farming system is one which has a net zero-or even beneficial-impact on the environment, allows coexistence with native species and supports the recovery of higher levels of biodiversity, ensures high welfare of the animals, ensures the welfare of the local community, and is profitable. Current systems for livestock production typically take a heavy toll on the environment, with forests felled for pasture and the growth of feedcrops (Ramankutty and Foley, 1999; Foley et al., 2011; FAO, 2022). In addition to contributing to the removal of carbon sinks and requiring large quantities of water resources (Mekonnen and Hoekstra, 2012), livestock production is a major source of greenhouse gases and other pollutants and can exacerbate soil erosion (Godfray et al., 2018).

Livestock provides approximately one third of the protein consumed in the human diet (Suryawanshi et al., 2017). The production of livestock also provides significant employment worldwide, and the trade of animals and their products are core contributors to the economies of many countries (Organisation for Economic Co-operation and Development (OECD), 2015). Government and industry face multiple competing demands to: increase efficiency and productivity; ensure food is safe and nutritious; adapt to climate change; maintain high environmental and animal welfare standards; and manage fluctuating prices and trading patterns. Meeting these challenges by running a sustainable system requires complex decision-making, drawing on evidence from the whole supply chain and beyond.

The urgent reform of the agri-food systems of the world is central to the United Nation's Millennium and Sustainable Development Goals (UN General Assembly, 2015). Of particular focus are the grand challenges of achieving global food security, as well as mitigating the deleterious effects of climate change and other forms of environmental deterioration. The drivers for change in the way food is produced in low, middle, and high-income countries share the common goal of increasing outputs in a way that minimises environmental harm, principally by reducing agricultural inputs. There are also drivers for change in the type of foods produced in terms of improving nutritional value, as well as moving away from large-scale monocultures, and providing a wider variety of alternatives. The reform of agricultural practices is also of special relevance to several other Sustainable Development Goals, including the eradication of poverty, the empowerment of women, and ensuring good health and well-being. Meeting these challenges and others facing the agricultural and food and non-food systems will require inter- and trans-disciplinary approaches that can deal with complexity, allowing for an integrated solution for the global supply system. Digitalisation of livestock production through smart agri-technologies offers a route to meeting these challenges (Neethirajan and Kemp, 2021).

Technological innovations in agriculture have opened a range of capabilities that help to increase production and efficiency in everyday processes through machine observation and recording of data. The use of precision farming technologies is projected to rise by over 13% by 2025, achieving a global market of over 10 billion US dollars (Xinhuanet, 2018). This paper will discuss the advantages and challenges of applying smart agri-systems in practice, using the pig industry and the recently developed National Pig Centre (a flagship pig research facility in the UK) as an example.

What is a smart agri-system?

Smart agri-systems are the connection of technologies to improve the quantity and quality of production, whilst optimisinglabour requirements. Smart agri-technologies include sensors (e.g. measuring temperature, light, water), location systems (e.g. Global Positioning System; **GPS**), communication systems (e.g. mobile software), supply chain tracking (e.g. software allowing the tracking of products from farm to consumer), robotics (i.e. technologies that can assist farmers with operations, for example labour intensive tasks such as fruit picking), and artificial intelligence (i.e. computer systems capable of intelligent tasks, such as decision making). Connecting these smart agri-technologies is termed the Internet of Things.

Internet of Things enables connection between sensors and machines that can alter conditions on the farm in response to the data received. Connecting smart agri-technologies has the potential to enable greater oversight, control, and potential efficiency savings through the generation of large-scale databanks for big data analytics and forecasting and intervention.

Precision livestock farming

Precision livestock farming (**PLF**) is the use of smart technologies to manage livestock. Precision livestock farming methods take precise measurements of individual animals to automatically monitor their states or conditions for the purpose of improving production, health, and welfare. Traditionally, decision making in livestock production is based principally on the experience of the farmer (García et al., 2020). There is an increase in the use of technology in livestock systems to monitor production and performance, with the aim of optimising, whilst simultaneously reducing, workload for farmers. The aim of PLF is to provide farmers with tools to enable continuous and remote monitoring of their animals and the farm environment (Berckmans, 2006). The quantitative data obtained from PLF technologies can help to inform decision making. Data can be obtained in real-time and analysed fully or semi-automatically using machine learning, control systems, and information and communication technology approaches (Banhazi et al., 2012).

There are a wide range of PLF technologies available that have been designed to optimise production processes in the pig sector (Benjamin and Yik, 2019). These include camera systems for assessing BW, behaviour and activity (White et al., 2004, Nasirahmadi et al., 2015); thermal cameras for body temperature (da Fonseca et al., 2020); load cells of varying types for measuring feed intake, BW, and gait (Schinckel et al., 2005); flow meters for water intake (Madsen and Kristensen, 2005); microphones for monitoring coughing and vocalisations (da Silva et al., 2019); accelerometers for activity (Cornou et al., 2011); photoelectric sensors to detect lameness (Besteiro et al., 2018); Radio frequency identification (RFID) for individual identification and tracking (Porto et al., 2012); non-contact body temperature sensors (Schmidt et al., 2014); and GPS for location. Regarding animal-based welfare indicators in pigs, 83 commercially available PLF technologies have been identified in the published literature (Gómez et al., 2021). Despite the number of technologies available, few have been fully validated. Gómez et al. (2021) report that only 5% of the 83 identified technologies had been both internally and externally validated (i.e. determining the predictive accuracy of the technology using both individuals from the same and different populations as was used to develop the technology). To ensure the accuracy of PLF technologies across different systems, the technologies must also be tested across different ages, breeds, and in different housing environments, all of which can impact the accuracy of the sensors.

To date, the application of PLF technologies has primarily been in intensive farming systems (i.e. systems with high levels of input and/or output per unit area). Precision livestock farming technologies have been less frequently applied to extensive farming systems (i.e. systems with low levels of input and/or output per unit area). This is due to the challenges of collecting data in extensive farming systems, namely that they typically cover large, heterogeneous and highly changeable environments (Wishart et al., 2015, Morgan-Davies et al., 2017; di Virgilio et al., 2018). As 91% of global livestock are extensively reared, applying PLF technologies to extensive farming systems has clear benefits for global animal health and welfare, as well as landscape conservation (Kokin et al., 2007), and minimising the impact of livestock on the environment (Misselbrook et al., 2016).

The vast majority of the PLF technologies have been developed independently of other technologies (though see for example di Virgilio et al., 2018). This gives a focused view on the parameter being measured but does not allow a broader, systems view. Tackling this issue is challenging, as will be discussed.

Advantages and challenges of adopting a smart agri-system approach

Smart agri-systems offer an integrated approach to tackling agriculture challenges across the whole supply chain (i.e. from source to consumer). Using and applying the cutting edge of precision farming technologies and computer science, combined with in-depth insights from data analytics, business, and policy allows a cross-modal, multiperspective view on complex challenges. Smart agri-systems provides solutions for farmers facing multiple competing expectations. Multi-objective decision-making is only possible with a full view of the outcomes in the different spheres of importance for agriculture, such as ecological sustainability, economic viability, supply chain efficiencies and the effects of potential threats to resilience. A smart agri-systems approach allows agribusiness to tackle multi-objective decision-making for the challenges of sustainable development with a strong evidence base and quantifiable risk. There are several challenges to adopting smart agri-systems approaches, including the challenges in data accessibility, sharing across businesses, and ownership, as well as ensuring technologies are valid and can be applied across different farming systems. The advantages and challenges of adopting smart agri-system approaches will be discussed in the context of within and beyond the farmgate. We use examples from crop production, and specifically regarding post farmgate, we discuss the benefits and challenges of digital twinning for livestock production.

Within the farmgate

Smart agri-systems present opportunities within the farmgate to improve farming operations, production, and outputs. In terms of livestock production, PLF technologies have been integrated in poultry farming to (i) collect real-time continuous data on flock behaviour and environmental conditions through sensors and cameras, (ii) analyse and learn from this data through artificial intelligence and machine learning, and (iii) alert farmers of disease outbreak or alter environmental conditions to optimise production, health, and welfare (e.g. https://www.optifarm.co.uk). In dairy farming, PLF technologies and Internet of Things can collect data on food and water consumption, health (e.g. automatic milking devices able to detect disease), behaviour, and activity levels (e.g. wearable technology, such as https://www.icerobotics.com/). Integrating this data can aid farmers to improve milk production and reproduction, as well as the health and welfare of cows (Akbar et al., 2020). Although there is an increasing range of precision livestock technologies available, to date the widespread use of multiplatform sensors and digitalisation in livestock production has not reached the level seen in precision agronomy (i.e. the automatic monitoring of individual fields or crops). Looking briefly at progress on this front is informative for near-future potential in livestock production. In precision agronomy, forecasting and predictive analytics can use data to support decision making relating to soil management, crop maturity, and the best times to sow and harvest a crop. This can be seen in practice in the use of machine learning on remotely sensed data to forecast crop production and nitrogen levels (Chlingaryan et al., 2018).

Machine learning can also be used to predict crop growth in smart greenhouses using data from a multisensor network integrated by Internet of Things (Kocian et al., 2020). Similarly, wireless sensor networks can provide a disease monitoring service for early warning of emerging health problems (Khattab et al., 2019). Deep learning technology, using neural network models, has also been applied to design automated fruit detection systems and automated harvesting using multimodal imagery of mangoes (Koirala et al., 2019), apples (Kang and Chen, 2019), and cotton (Li et al., 2017). Smart drone systems have been developed to provide identification and monitoring services over larger areas, allowing surveillance of crop disease, weeds, and irrigation issues (Mogilli and Deepak, 2018). Decision support systems, data analysis, and mining have become a critical method of managing precision agronomy (Zhai et al., 2020); these systems are used to enable producers to meet multiple simultaneous requirements, such as production performance, finances, and market dynamics (Narra et al., 2020).

Precision agronomy faces many of the same challenges as PLF, such as investment, integration ability of technologies, and data quality, validity, and sharing, as we will discuss in relation to livestock farming below. Precision agronomy also has unique challenges due to the differences in the scales and environmental conditions of crop production, as the technologies must be able to communicate across large ranges, with adequate remote power supplies, and function in harsh conditions (see Villa-Henriksen et al., 2020 for review).

Beyond the farmgate

The benefit of extending the smart system beyond the farmgate is that it allows progress and performance to be tracked all the way through from preplanting to consumption, building up a rich picture over time of peak performance and the nature of performance (e.g. the conditions that lead to optimal performance and the problems that reliably cause performance to falter and to what extent). Post farmgate, sensor arrays, tracking, and auditing technologies can be combined to allow aggregation of data across the supply chain, encompassing information from logistics, consumer behaviour, health outcomes, trade, and business to provide oversight of the broader system (Torky and Hassanein, 2020). There is potential to link multiple farms or supply chains, learning from experience encoded in the reams of data collected every day, leading to a future where the data allows sites to communicate, to self-correct, to improve health, welfare, and performance, and to ultimately become more efficient, effective, and sustainable. Blockchain technology, a decentralised, distributed ledger for storing time-stamped transactions across a peer-to-peer network (Torky and Hassanein, 2020), can assist in this linking, and is recognised as bringing other benefits such as traceability (Casado-Vara et al., 2018) and assurance of provenance (Mann et al., 2018).

For most supply chains, the aggregation of data across the supply chain (from source to consumer) will require data sharing agreements between different businesses in the chain. This is typically a particularly difficult issue unless the information being shared has minimal commercial value. Data accessibility, sharing, and ownership is perhaps the largest issue at present (see Spanaki et al., 2021 for overview). Even for a company with multiple sensor platforms and with data inputs to be utilised, accessing and processing this data is not straightforward. Data is often spread over multiple locations, often not linked between spreadsheets and with some sensor outputs only accessible in raw format by contacting the technology provider (who are the data owners) and requesting access to the data. Beyond this accessibility issue in-house, sharing data with a third party is challenging whenever anything with commercial sensitivity is included. The issue of data is pressing; a smart system is only as good as the information on which it bases its learning. If data is incorrect, sparse, missing, inaccurate, unlinked, based on a limited range of conditions not representative of the wider industry, or lacking in sufficient detail, then the forecasts and outputs are likely to be lacking in quality too, and ultimately inaccurate.

Digital twinning

Smart agri-technology has the potential to allow the visualisation of farming systems to predict how changes might impact the system (e.g. in terms of production, environmental impact, or animal health and welfare). Most recently, digital twinning has been explored for use in precision agronomy, to combine various technologies such as artificial intelligence, Internet of Things, augmented reality, communication and embedded technologies, data analytics, security, and cloud computing (Qi et al., 2021). Digital twinning is defined as a virtual model (i.e. digital replica) of a system over the system's lifecycle. A digital twin can replicate the processes of a system, allowing it to be used for designing, monitoring, and improving operations of its real-life counterpart, ultimately providing a realistic experience for end-users (Barricelli et al., 2019, Sreedevi and Santosh Kumar, 2020). Digital twinning of all or part of a supply chain allows a range of manipulations to be made *in silico,* to identify which changes lead to optimal outputs across multiple domains (e.g. identifying optimal outputs for production, environmental footprint, welfare, and nutritional quality). This is particularly advantageous when a producer is considering making a change to their standard practices but wants to understand whether the change will result in improvements and whether there may be some unintended negative consequences of the change. Digital twinning and simulations allow these alternative scenarios to be modelled before any capital investment has taken place, with economic, environmental, health or performance as the key output. For example, digital twinning of pig production systems could be used to forecast the potential benefits and disbenefits of making changes to parts of the production system, such as the purchase of equipment to neutralise emissions from slurry and hence reduce the environmental footprint of production, to determine whether the system is likely to be viable. In a more expansive context, and with particular relevance to outdoor or circular farming systems, digital twinning could be used to map soil types, drainage and local climate to investigate the likely impacts on soil health of outdoor production, or to quantify the potential risks associated with leaching of waste into the environment. Digital twinning could also be used to forecast the potential disease risk profile for a range of infectious and non-infectious diseases under different short- and medium-term scenarios, such as variations of temperature gradients, stocking densities, breeds, and animal nutrition. The simulations could inform farmer decisions regarding genetics, climatic conditions, and animal nutrition.

The application of digital twinning in agriculture is still very much in its infancy (see Pylianidis et al., 2021 for review), perhaps owing to remote farm locations and inadequate communications, highly dynamic environmental conditions, lack of finance, and a lack of willingness to share data. These all combine to make the task certainly more challenging, but not insurmountable. It has been demonstrated for hydroponics (Sreedevi and Santosh Kumar, 2020) and in modelling the production processes in a malt house (Dolci, 2017), with the aim of outlining the optimal settings and timings to achieve the desirable result of high alcohol content in the final stages of production, based on environment data as a predictor of temperatures within the grain pile.

How can a smart agri-system approach be applied to the pig industry and what are the current barriers to adoption?

To encourage adoption of smart agri-systems, we need to address the question: to what extent can the precision technologies and smart agri-systems approaches being developed for precision agronomy and other industries be used to benefit the pig industry? A significant problem for all pig producers is the inherent performance variability within each herd which is associated with substantial losses. Many pig producers are interested in optimising their understanding of pig performance all the way through the production process, from preconception through to consumer. To do this, it is recognised that there is a need for robust statistical data and scientific evidence, to illuminate the factors that lead to variation in performance between pigs and between farms, with a view to raising health and welfare standards on farm. Data collection on farm is still largely reliant on stockpersons taking measurements and inputting these into a series of spreadsheets, which is error-prone and time consuming. Automated data capture systems both on farm and downstream in the supply chain address these issues, but one challenge will be to gain buy-in from the affected stakeholders at a sufficient level. This may be achieved by demonstrating effectiveness relative to current processes.

Smart agri-systems will allow us to better understand the supply chain and wider food system more broadly, with knock-on benefits for policymakers, retailers, and consumers. However, as is often the case, the farmer ultimately puts in the labour, shoulders the expenditure and receives little in return. Nevertheless, there are also benefits of using a smart agri-system for farmers too. For example, accurate forecasting tools means farmers are better able to predict the date their stock will be ready to go to the abattoir, offering reassurance to the customer and meaning there are fewer inefficiencies in outgoings. In practice, smart agri-tools can easily be used to reduce within-batch variation in performance, helping to reduce wastage and increase efficiencies in the system. With tight profit margins, such efficiency savings are critical to supporting a financially viable business. Efficiency savings also allow reinvestment opportunities into the business to support further sustainability improvements.

To understand the extent that precision technologies and smart agri-system approaches can benefit the pig industry, we must consider some of the key issues that may be barriers to uptake at present. Firstly, the usefulness of PLF technologies is limited when that do not easily ‘talk’ to each other, or feed directly into standard farm software, as the data cannot be integrated and analysed without the support of a dedicated data analyst in house capable of handling potentially massive datasets. Whilst some of the largest companies may have this skillset in house, the vast majority will not.

Secondly, the lack of thorough and extensive validation of many developed and available PLF technologies for different stages of production, different types of system, and different environments means that reliability and accuracy is likely to be compromised when in dynamic commercial practice. These technologies need to be investigated across a much broader set of conditions to quantify accuracy and false detection rates.

Thirdly, whilst there are certainly pockets of rich data in existence across the pig industry - with some producers keeping highly detailed batch-level data (and in some cases, sub-batch or individual level) throughout the production cycles - this is not the case across the industry as a whole. Due to complications of data sharing, commercial sensitivities, data ownership and permissions, much of the data that does exist is difficult to knit together into a bigger picture. This could be overcome with precompetitive agreements to collaborate to find working solutions to real black box, complex problems that are far larger than any one company can solve alone, such as the move towards developing net zero farming solutions.

Finally, one further potential barrier could be the high level of investment needed to scale these technologies. Investment in these technologies presents a significant risk, as most are still emerging and have not yet proved their worth to the livestock industry. To encourage commercial investment in the development of technologies and demonstrated applications of technologies in this space, governments need to offer incentives and support to carry some of that risk and encourage creative innovation.

A case study using smart agri-systems for enhanced sustainability - the National Pig Centre at the University of Leeds, UK

The University of Leeds' farm is a commercial and research farm occupying approximately 317 hectares with a mix of livestock and arable farming. Around three quarters of the land is used for arable farming, including wheat, barley, and oil seed rape, with smaller plots used for potatoes, peas, and agroforestry. In 2016, the farm also included a small commercial unit with intensive indoor pig production. Academic research at the pig unit was focussed on animal nutrition, gut health, and performance with some work on animal health and welfare. Professor Helen Miller secured significant investment to build a new flagship pig research centre on the site of the former unit through her involvement in the Centre for Innovation Excellence in Livestock (a national agri-technology collaboration between industry, government, and academia). This new facility would become the National Pig Centre. The National Pig Centre has been operational since October 2020 and hosts both an indoor and outdoor production system (the outdoor system is part of a crop rotation cycle within the arable farm) on a commercial scale, with a capacity of 660 sows (220 outdoor and 440 indoor). The combination of an outdoor sow unit with an indoor system is unique in Europe, enabling a direct comparison of the different rearing systems.

The National Pig Centre's goal is to be a demonstrator and testbed site for integrated smart agri-systems solutions for the pig industry – developing, testing, and applying technology solutions to deliver commercially applicable, long term sustainable practices for animal, environmental, and public health. By doing this, it will demonstrate both the benefits and pitfalls of a smart agri-system solutions for farmers and the wider supply chain, and working closely with commercial and research partners, will allow the de-risking of new and emerging solutions in a highly instrumented, but commercial farm environment.

Through collaborations with the Leeds Institute for Data Analytics, the Priestley Centre for Climate Change, Sustainability Institute and collaborators in engineering and computer science, the National Pig Centre is developing a smart agri-system approach to investigating sustainable approaches for future pig production, including renewable energy, circular economy approaches and regenerative agriculture practices. Our aim is to achieve net zero production by 2030. To reach this target, our focus is on increasing sustainability and increasing efficiency. We are using a smart agri-system approach to quantify and mark our progress across the whole system. For this, we are utilising multiplatform PLF technologies (camera systems, load cells, flow meters, RFID, and precision nutrition capabilities for distributing a range of individual-specific diets), alongside environmental monitors in house (light time and intensity, indoor and outdoor temperature, and ventilation monitors that automatically adjusts depending on production stage and stocking density), and on farm (automatic weather stations that records air, temperature and rainfall, soil moisture probes, and eddy covariance flux towers to analyse CO_2 fluxes). These technologies continuously capture individual and pen-level data, which will then be integrated and, ultimately, processed and analysed using machine learning algorithms. This information enables the identification of key factors contributing to performance and welfare, as well as continuous monitoring of the environmental footprint to allow investigation into alternative approaches to drive down the sector's greenhouse gas emissions. As the farm is run as a commercial unit, financial and economic information are also able to be collected, analysed, and integrated with the other data streams. This has the potential to demonstrate the economic advantages of smart agri-system approaches and encourage the adoption and buy-in of smart agri-system technologies. The data will also be accessible for further analysis, deep learning, and digital twinning. For example, in terms of pig production, the National Pig Centre has the potential to use the camera technology to monitor pig behaviour in real time. The data can be processed and analysed using machine learning algorithms to detect behaviours indicative of potential outbreaks of disease or undesirable behaviours such as tail biting that may compromise pig health and welfare, and production outputs. In the situation where the algorithms detect indicators for a potential outbreak of disease, then through the Internet of Things, the farmer could be notified to treat or alter management methods. In a prospective epidemiological approach (albeit in a single farm), batches can be followed from gestation through to the abattoir, collecting vast quantities of data on healthy pigs as well as data on disease occurrences in the herd. The data collected by the environmental monitors in house can be analysed alongside the prospective herd health and welfare data to determine associations between environmental conditions, feed and water intake, diet, genetics, and other factors with the outbreak of undesirable health and welfare conditions. Given the size of the herd, the number of sensors and the frequency and resolution of data capture, very large databases are created in a very short period of time. This data can be used in multiple ways – for epidemiological analysis, for performance metrics, and for forecasting and simulation development and digital twinning. Digital twinning could be used to assess a huge variety of alternative scenarios, as discussed previously, such as forecasting the impact of directly or indirectly altering any of the variables for which the databank is collected. As such, it can be used to model the potential impact on tail biting of switching diets, or of altering vent angle based on local weather conditions. Fig. 1 illustrates the linking of smart agri-system technologies both within and beyond the farmgate at the National Pig Centre.

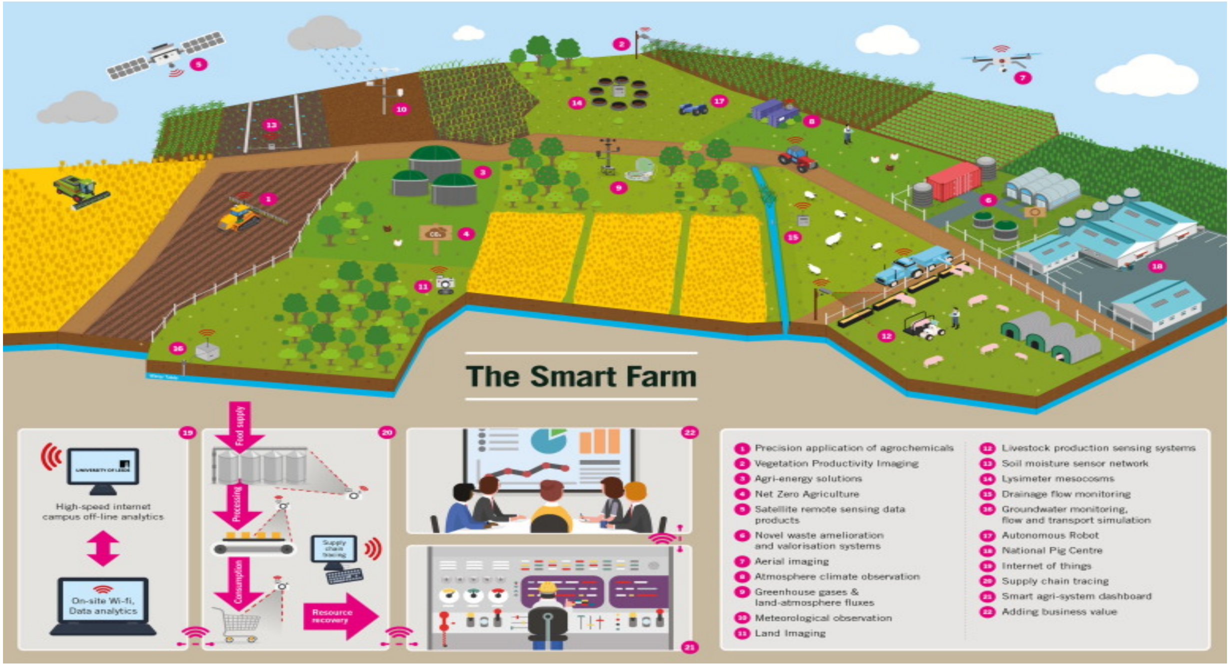

Fig. 1. Illustration of a smart farm, modelled on the University of Leeds farm facility and including the National Pig Centre, that integrates smart agri-system technologies within and beyond the farm gate. Different technologies are represented by a numerical code included on the figure as follows: 1 Precision application of agrochemicals; 2 Vegetation Productivity Imaging; 3 Agri-energy solutions; 4 Net Zero Agriculture; 5 Satellite remote sensing data products; 6 Novel waste amelioration and valorisation systems; 7 Aerial imaging; 8 Atmosphere climate observations; 9 Greenhouse gases and land–atmosphere fluxes; 10 Meteorological observation; 11 Land imaging; 12 Livestock production sensing systems; 13 Soil moisture sensor network; 14 Lysimeter; 15 Drainage flow monitoring; 16 Groundwater monitoring, flow and transport simulation; 17 Autonomous robot; 18 National Pig Centre; 19 Internet of Things; 20 Supply chain tracing; 21 Smart agri-system dashboard; 22 Adding business value.

Additionally, in terms of environmental impact, the National Pig Centre is currently a demonstration case-study as part of the European Union (EU) project ClieNFarm (https://cordis.europa.eu/project/id/101036822), which aims to test and evaluate integrated smart agri-systems solutions that can contribute to the reduction of greenhouse gas emissions. To increase biosecurity by reducing footfall from visitors on site, we are also collaborating with the Centre for Immersive Technologies to develop an augmented reality tour. The technologies at the National Pig Centre can be used both to find efficiency savings and to test potential investment opportunities for improvements to production, environmental impact, and animal health and welfare.

CONCLUSIONS

Digitalisation of the pig industry offers huge opportunities for maximizing efficiencies, reducing waste, trialling alternative, net zero production systems before spending a penny on capital investment, preventing animal disease, and maximizing animal welfare. A smart agri-systems approach allows producers and actors in the wider supply chain to tackle multi-objective decision-making for the challenges of sustainable development with a strong evidence base and quantifiable risk. It has the potential to provide significant insight and forecasting support for farmers. Achieving such a system will require significant changes in the current pig industry, both for the commercial producers and the allied industries. To encourage adoption of smart agri-systems in the pig industry we need to (i) improve data integration and processing methods to make using digital systems simpler for those without an analytical background, (ii) more extensively validate available PLF technologies to thoroughly understand their accuracy and false detection rate, (iii) improve data sharing, and (iv) increase the opportunities for de-risking investment in innovation to allow industry to co-develop technologies that will support their longer term goals for sustainable production.

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